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3D OBJECT CLASSIFICATION IN BAGGAGE COMPUTED TOMOGRAPHY IMAGERY USING RANDOMISED CLUSTERING FORESTS

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ABSTRACT

We investigate the feasibility of a codebook approach for the automated classification of threats in pre-segmented 3D baggage Computed Tomography (CT) security imagery. We compare the performance of five codebook models, using various combinations of sampling strategies, feature encoding techniques and classifiers, to the current state-of-the-art 3D visual cortex approach [1]. We demonstrate an improvement over the state-of-the-art both in terms of accuracy as well as processing time using a codebook constructed via randomised clustering forests [2], a dense feature sampling strategy and an SVM classifier. Correct classification rates in excess of 98% and false positive rates of less than 1%, in conjunction with a reduction of several orders of magnitude in processing time, make the proposed approach an attractive option for the automated classification of threats in security screening settings.

Index Terms— Classification, Bag-of-Words, Random forests, baggage CT

1. INTRODUCTION

The key role of baggage screening in the transport security domain has lead to an increased interest in the development of automated threat detection strategies. Traditionally, X-ray based 2D imaging technologies have been used for this purpose [3]. Due to variations in object orientation, clutter and density confusion, contraband objects are often challenging to detect in 2D X-ray images. Recently, the use of 3D Computed Tomography (CT) based screening systems have become more widespread as a means of addressing these limitations. Typically, Dual-Energy Computed Tomography (DECT) scanners are used to allow for material-based detection of explosives [4]. This primary, non-object-recognition based objective of typical baggage-CT scanners, coupled with the demand for high throughput, means baggage-CT imagery is typically of a much poorer quality than that encountered in the medical domain and presents with substantial noise, metal streaking artefacts and poor voxel resolution [5] (Figure 1).

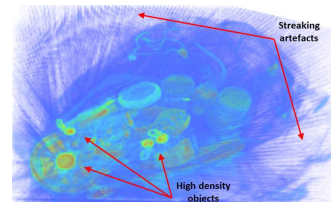


Fig. 1: Cluttered baggage-CT scan with streaking artefacts.

Prior work related to the automated classification of objects within complex non-medical 3D volumetric imagery is limited. Chen *et al.* [6] address the classification of pistols in DECT imagery. The problem is, however, simplified to an examination of the characteristic cross sections and no experimental results are presented. Megherbi *et al.* [7] propose the use of a classifier-based approach using volumetric shape characteristics for the recognition of pre-segmented bottles in complex 3D CT imagery. While the study demonstrates reasonable results, only a very limited dataset is considered. Flitton *et al.* [1] have presented what may perhaps be considered the current state-of-the-art in automated object recognition in such complex 3D imagery. Particularly, a novel 3D extension to the hierarchical visual cortex model for object recognition [8] is used for the automated detection of threats in pre-segmented 3D CT baggage imagery. The approach is shown to outperform a traditional BoW approach with correct detection rates in excess of 95% and low false-positive rates. In addition to incurring a large computation overhead (in the construction of the cortex model), performance is shown to decline in the presence image noise and artefacts.

The Bag of (Visual) Words (BoW), or codebook, model [9] has enjoyed success in various object recognition and image classification tasks. BoW approaches require a clustering of the feature space to generate visual codebooks. Traditional clustering techniques (e.g. *k*-means clustering [10]) are computationally expensive when the feature space is large. Moosmann *et al.* [2] demonstrate state-of-the-art classification performance at a significant reduction in computational cost by constructing visual codebooks using Extremely Randomised Clustering (ERC) forests. Similar forest-based clustering approaches have enjoyed success in a variety of image classification, registration and segmentation tasks [11, 12, 13].

We extend the ERC forests to the previously unconsid-

ered domain of threat classification in volumetric baggage-CT imagery and evaluate its performance when used in conjunction with a variety of feature sampling strategies (sparse and dense) and classifiers (Support Vector Machines (SVM) and random forests). Our key contribution is an improvement over the state-of-the-art [1] true positive performance by 2 – 3%, a reduction in false positives of 40 – 70% and a reduction in processing time of several orders of magnitude.

2. METHODS

The following traditional BoW classification framework is adopted here [14]: 1) feature detection and description; 2) visual codebook generation and vector quantisation and 3) classification.

Feature detection and description: We compare the performance of two feature point sampling strategies: 1) a sparse sampling strategy (using the 3D SIFT interest-point detector [15] and 2) a dense sampling strategy (as recommended by [16]), whereby keypoints are sampled uniformly and randomly. An invariance to uniform changes in image scale is obtained by sampling interest points from three image scales [17] (as per [15]). At each of the scales a limit of $\tau_N = 0.006N$ on the number of randomly sampled points is enforced (where N is the number of voxels in the Gaussian scale-space image and τ_N is determined empirically). For the volumes used in this study ($N \sim 3 \times 10^5$), the proposed sampling strategy typically leads to an increase of two orders of magnitude in the number of sampled points compared to the original 3D SIFT keypoint detection approach of Flitton *et al.* [15] (making conventional k -means unsuitable).

Flitton *et al.* [18] have shown that simple density statistics-based descriptors outperform more complex 3D descriptors (SIFT [15] and RIFT [19]) in object detection within low resolution, complex volumetric CT imagery. In accordance with these findings, the Density Histogram (DH) descriptor [18] is used here. The descriptor characterises the local density variation at a given interest point as an N -bin histogram defined over a continuous density range. The optimal descriptor parameters are selected in accordance with [18, 20] and result in a 60-dimensional feature vector.

Visual codebook generation: The performance of two feature encoding techniques are evaluated and compared: 1) k -means clustering (using a sparse feature sampling strategy) and 2) Extremely Randomised Clustering (ERC) forests [2] (using both sparse and dense sampling strategies). ERC forests assign separate codewords to every leaf node in a given forest (i.e. a forest containing N leaf nodes, yields a codebook of size N). The BoW representation for a given image is obtained by accumulating the codeword counts after applying the forest to all the descriptors in the image. The resulting histogram of codewords is then used in subsequent classification in the same way as any standard BoW model. In contrast to k -means clustering, ERC forests are supervised. Trees are trained in a top-down recursive fashion [21] using

Alias	Sampling	Codebook	Classifier
Codebook1	Sparse SIFT	k -means	SVM
Codebook2	Sparse SIFT	ERC	SVM
Codebook3	Sparse SIFT	ERC	Random forest
Codebook4	Dense	ERC	SVM
Codebook5	Dense	ERC	Random forest
Cortex	Dense	3D visual cortex	SVM

Table 1: Summary of classification techniques compared.

a set of labelled training descriptors, where the labels are obtained from global image annotations (i.e. all descriptors from a given image share the same label). A simple thresholding function is used as the node split function for all internal nodes of the forest:

$$f(v_i, \theta_j) = \begin{cases} 0 & v_i < \theta_j \\ 1 & \text{otherwise} \end{cases} \quad (1)$$

where $v_i, i = 1, \dots, D$ is a single feature attribute selected from a D -dimensional descriptor vector $\mathbf{v} \in \mathbb{R}^D$ and θ_j is a scalar valued threshold ($D = 60$). The optimality criterion used for node splitting is the classical Information Gain (IG) [22]. Randomness is injected into the trees by considering a fixed-size random subset of the available node split function parameter values at each node.

Classification: The performance of two classifiers are compared using the aforementioned combinations of sampling strategies and feature encoding techniques: 1) an SVM classifier using a Radial Basis Function (RBF) kernel [23] and 2) a random forest classifier using a linear classifier as the node split function (as per [24]):

$$f(\mathbf{v}, \theta_j) = \begin{cases} 0 & \mathbf{n}^T \mathbf{v} + b \leq 0 \\ 1 & \text{otherwise} \end{cases} \quad (2)$$

where $\theta_j = \{\mathbf{n}, b\}$; \mathbf{n} is a vector of the same dimensions as \mathbf{v} and b is a constant. The vector \mathbf{n} is randomly populated with values in the range $[-1, 1]$ and the constant b is randomly selected. Test samples are classified according to the average of the individual leaf-node predictions [21].

The six classification techniques that are evaluated and compared in this study have been summarised in Table 1.

3. RESULTS

The proposed techniques were evaluated on the classification of two target objects (handguns and bottles) in cluttered 3D baggage-CT imagery obtained on a CT-80DR dual-energy baggage scanner manufactured by Reveal Imaging Inc., which produces volumes with low anisotropic resolutions (1.56x1.61x5mm). We considered only the high-energy (nominal tube voltage of 160kVp), filtered-back projection [25] reconstructed CT images. Target objects were scanned in random poses to obtain rotational invariance and were manually isolated prior to feature extraction (Figure 2). The two object classes were considered independently of one another. All non-target objects were considered as clutter (e.g.

Method	Class	TPR (%)	FPR (%)	Precision	Time (s)
Codebook1	Handgun	97.34 \pm 3.41	1.81 \pm 1.70	0.942 \pm 0.053	-
	Bottle	89.33 \pm 5.52	3.01 \pm 1.44	0.932 \pm 0.029	
Codebook2	Handgun	98.60 \pm 1.52	0.70 \pm 0.31	0.976 \pm 0.028	94.36
	Bottle	93.31 \pm 3.10	1.88 \pm 1.22	0.958 \pm 0.042	
Codebook3	Handgun	95.61 \pm 3.30	0.61 \pm 0.72	0.978 \pm 0.023	92.83
	Bottle	94.23 \pm 3.31	3.70 \pm 2.00	0.921 \pm 0.037	
Codebook4	Handgun	99.71 \pm 0.51	0.28 \pm 0.21	0.990 \pm 0.013	186.89
	Bottle	98.88 \pm 0.68	0.60 \pm 0.25	0.987 \pm 0.021	
Codebook5	Handgun	97.74 \pm 2.13	0.57 \pm 0.53	0.979 \pm 0.018	161.47
	Bottle	97.44 \pm 0.66	0.69 \pm 0.43	0.985 \pm 0.009	
Cortex [1]	Handgun	96.81 \pm 2.64	1.10 \pm 0.93	0.962 \pm 0.029	$> 3.6 \times 10^3$
	Bottle	96.62 \pm 3.23	1.01 \pm 1.63	0.977 \pm 0.034	

Table 2: Overall classification performance for six tested methods. Optimal performance indicated in bold.

clothing, books, mobile phones etc.) and were chosen to provide an environment that is representative of that encountered within the transport infrastructure. The handgun and bottle datasets consisted of 1255 volumes (284 target; 971 clutter) and 1704 volumes (534 target; 1170 clutter) respectively as per [1, 20]. 10-fold cross-validation testing was performed using the identical data and data-splits used in [1], allowing for a direct performance comparison between methods.

The cost C and the kernel width γ of the RBF kernel used in the SVM classifier were optimised using a standard grid-search cross-validation procedure [26]. K -means clustering-based codebooks were generated using $k = 1024$ clusters for the handgun target class and $k = 512$ clusters for the bottle target class. A kernel-based cluster assignment methodology was adopted for both classes (with kernel widths of $\sigma = 0.04$ and $\sigma = 0.08$ for handguns and bottles respectively). These parameters were based on the extensive experimental comparison performed on the same dataset in [20]. Internal nodes in the ERC forests were optimised by performing 30 tests at each node - this value was fixed for all nodes. Trees were grown to a maximum depth of $D_T = 10$, with a lower bound of $IG_{min} = 10^{-4}$ on the information gain. The settings resulted in trees with approximately 1000 leaf nodes each. For a forest containing $T = 25$ trees, codebooks therefore typically contained approximately 25000 codewords. Classification forests were composed of 30 trees, grown to maximum depths of $D_T = 20$, using a lower bound of $IG_{min} = 10^{-4}$ on the information gain. It was found that using these settings resulted in tree growth terminating prior to maximum depth and thus no tree pruning was performed.

Experiments were performed on an Intel Core i5 machine running a 2.30GHz processor with 6GB of RAM. The random forest methods were implemented in C++ using the Sherwood decision forest library [27]. The processing times, measured over the entire 10-fold cross-validation procedure and averaged over the two experiments (bottles and handguns), are recorded in the final column of Table 2. Use of the average is justified by the fact that all subvolumes considered in this work are of similar sizes and hence result in similar-sized

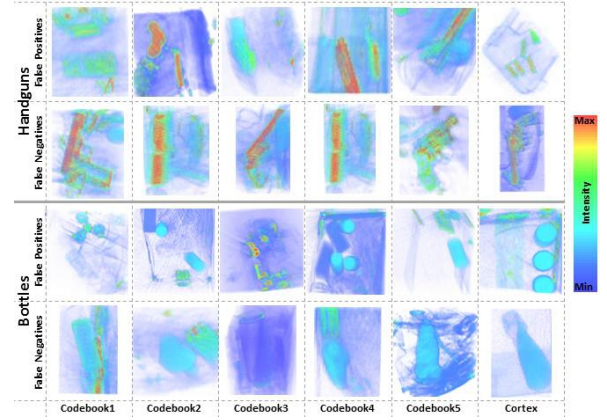


Fig. 2: Classification errors. High-density objects and low-density handgun handles indicated.

codebooks (codebook sizes being the main factor impacting processing times). As the Codebook1 and Cortex approaches were not directly implemented in this study, their corresponding processing times are not known. It is known, however, that the processing time for the construction of the 3D visual cortex model using the current dataset, is in the order of hours [20]. As expected, the sparse feature sampling strategy (for both the SVM and random forest classifiers) led to considerably lower processing times ($\sim 90s$) relative to the dense sampling strategy ($\sim 175s$). The random forest classifier resulted in marginal improvements in the processing times for both sampling strategies ($\sim 2s$ for sparse sampling; $\sim 25s$ for dense sampling).

Table 2 summarises the results of the experiments averaged over the 10 folds. While there was no major variance in the handgun classification performance across all six methods, the most significant improvements over the baseline Cortex approach [1] (TPR = 96.81%; FPR = 1.10%) were produced by the Codebook2 (TPR = 98.60%; FPR = 0.70%), Codebook4 (TPR = 99.71%; FPR = 0.28%) and Codebook5 (TPR = 97.74%; FPR = 0.57%) approaches, each of which employ ERC forests. The use of the random forest classifier resulted in a decline in performance, particularly in terms of

the number of false-negative classifications (see Codebook2 (SVM) vs. Codebook3 (random forest) and Codebook4 (SVM) vs. Codebook5 (random forest)).

The codebooks constructed using sparse feature sampling resulted in the highest bottle FPRs (Codebook1: FPR = 3.01%; Codebook2: FPR = 1.88% and Codebook3: FPR = 3.70%). Nonetheless, the use of ERC forests did result in an improvement over k -means clustering (Codebook1 vs. Codebook2). The most significant improvements over the baseline Cortex approach (TPR = 96.62%; FPR = 1.01%) were produced by the densely sampled codebooks: Codebook4 (TPR = 98.88%; FPR = 0.60%) and Codebook5 (TPR = 97.44%; FPR = 0.69%). Similarly to the handgun experiments, the SVM classifier outperformed the random forest classifier (see Codebook2 vs. Codebook3 and Codebook4 vs. Codebook5). The performance gains of all four ERC forest-based codebooks over the traditional k -means codebook (Codebook1 - TPR = 89.33%; FPR = 3.01%) were more substantial than observed in the handgun experiments. Codebook4 (ERC forest, dense feature sampling and SVM classifier) produced the optimal performance in both the handgun and bottle experiments with improvements over the state-of-the-art Cortex approach of $> 3\%$ and $> 2\%$ in the TPR for handgun and bottle classification respectively and reductions of 70% and 40% in the corresponding FPR.

Figure 2 illustrates several misclassifications produced by each of the six methods. In terms of false-positive (FP) classifications, the only obvious trend in the handgun examples is the presence of high-density objects (coloured red/orange), particularly in the false-positive instances for the ERC forest codebooks (Codebook2, Codebook3, Codebook4 and Codebook5). The k -means clustering codebook (Codebook1) and the Cortex false-positives bear minimal similarities to the handgun training data. Codebook2 and Codebook4 produced false-negative handgun classifications for handguns containing low-density handles relative to the barrels - a property which was not evident in the misclassifications of the other four methods (note also that Codebook2 produced additional false-negatives which did not exhibit these characteristics).

Closer examination of the bottle misclassifications has not indicated any obvious sources of error or trends within the false-negative classifications (i.e. missed bottles). The two most obvious consistencies in the false-positive bottle classifications (for all six methods) are: 1) the presence of items with circular cross sections similar to that of a full bottle and 2) the presence of image regions that are similar in density to the liquids used in the training set. It is worth noting that these observations are in accordance with those made in the previous works of Flitton *et al.* [1, 20].

While codebook approaches do not capture spatial/geometric relations between codewords, the dense sampling strategy appears to compensate for this - illustrated by the gain in performance of Codebook4 (dense sampling with SVM) over Codebook2 (sparse sampling with SVM) and Codebook5

(dense sampling with random forest classifier) over Codebook3 (sparse sampling with random forest classifier). It is likely that the k -means codebook classification results (Codebook1) would improve using dense sampling, but at a significant increase in computational cost. Furthermore, it is suspected that these gains would not match those of the ERC forest codebooks using dense sampling, judging from the superior performance of Codebook2 (ERC forest) over Codebook1 (k -means clustering) when using identical sparse features.

Despite the marginal increase in processing time, the SVM classifier consistently outperforms the random forest classifier in terms of classification accuracy (Codebook2 vs. Codebook3 and Codebook4 vs. Codebook5). This is in contrast to the prior image classification literature [28], although there does exist prior work (especially within the bioinformatics domain) that demonstrates that SVMs consistently outperform random forests in some classification problems [29, 30]. Furthermore, Criminisi [22] emphasises that the benefits of random forest-based image classification over popular techniques such as SVM and boosting are most prominent in multiclass and high-dimensional classification problems (as opposed to the two-class classification problems considered here). It is thus reasonable to conclude that SVMs are the preferred mode of classification within the current context.

It is worth noting that noise and metal artefact reduction [5, 25, 31] have not been considered in this work, demonstrating the robustness of the dense sampling-based codebook approaches to background noise and artefacts. It is expected that such techniques will be of greater importance in the automation of the segmentation process and is left as an area of future work.

4. CONCLUSIONS

A comparison of six methods for threat classification in low-resolution, cluttered volumetric baggage-CT imagery has been presented. We have demonstrated improvements over the state-of-the-art [1] of $> 3\%$ and $> 2\%$ in the TPR for handgun and bottle classification respectively and reductions of 70% and 40% in the corresponding FPR using a codebook constructed via ERC forests [2], a dense feature sampling strategy [16] and an SVM classifier [23]. This classification framework has not been considered previously in this domain. These significant improvements, together with a reduction of several orders of magnitude in processing time, make the proposed approach an attractive option for the automated classification of threats in 3D baggage security-screening imagery.

As this study has been restricted to two comparatively undemanding target objects (particularly the high-density handguns) and simplified by manual pre-segmentations, future work will consider the automated segmentation of baggage-CT imagery and an extension to multiple target classes.

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